Journal of Power Sources 245 (2014) 337–344

Contents lists available at SciVerse ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

A novel on-board state-of-charge estimation method for aged Li-ion batteries based on model adaptive extended Kalman filter

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HIGHLIGHTS

- Using a simple optimization algorithm to update electrical model of Aged Cells.
- Sensitivity analysis for battery model's elements and optimization algorithm.
- Validation with different current profiles.
- Validation with differently pre-aged cells.

ARTICLE INFO

Article history:
Received 22 April 2013
Received in revised form
12 June 2013
Accepted 18 June 2013
Available online 4 July 2013

Keywords:
Li-ion battery
State-of-charge estimation
Extended Kalman filter
Optimization

ABSTRACT

A battery management system needs to have an accurate inline estimation of SOC for each individual cell in the battery pack. This estimation process poses challenges after substantial battery aging. This article presents a novel method based on model adaptive extended Kalman filter (MAEKF) to estimate SOC for Li-ion batteries. Sensitivity analysis of the electrical model verifies that the accuracy of SOC estimated by EKF is sensitive to resistors used in the cell's electrical model. In order to get the best estimation, values of resistors are obtained in an optimization process in the MAEKF. This method uses the fact of two sudden changes in the cell's voltage derivative with respect to time while discharging current is constant. These two points are assumed as reference points in which their SOC can be determined from cell's chemistry. The optimization algorithm uses the derivative of the cell's measured terminal voltage to allocate SOC of 92% and 15% for two reference points in the V_{cell} equation and updates cell's electrical model. The algorithm's process is fast and computationally inexpensive, making on-board estimation practical. The obtained results demonstrate that by using this method the estimated SOC error for aged Li-ion cells does not exceed 4%.

1. Introduction

Rechargeable batteries have become one of the most popular candidates for electrical energy storage due to their ability to provide fast response to energy demand, ease for siting and their high energy efficiency. Under the global demand for reduction in greenhouse gas emissions, advanced battery systems are proposed for a wide range of applications varying from electrical vehicles (EVs) and hybrid electric vehicles (HEVs) all the way up to smart grids.

Li-ion batteries have several advantages over NiMH and lead acid alternatives and as such, have gained popularity as a research topic in industry and academia. These advantages include higher energy density, less weight, and longer cycle life. It is obvious that proper design, engineering and operation of these battery systems require an appropriate battery model [1]. There have been numerous models proposed in the literature that are sufficiently accurate to show the electrical behavior of Li-ion batteries [2–5]. Yet, these models rely on parameters of the battery such as the state of charge (SOC), which is an inner state of the battery [6], to function properly. How to accurately estimate the SOC under any working condition is still a challenge.

In recent years, great effort has been exercised to improve the accuracy of SOC estimation. The coulomb counting method is the

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http://dx.doi.org/10.1016/j.jpowsour.2013.06.108

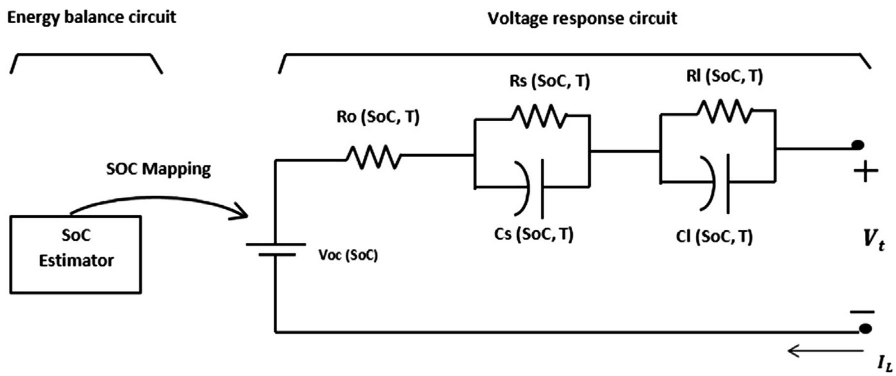

Fig. 1. Schematic diagram of the electrical model [5].

most common method used to estimate SOC [7]. However, this method has several drawbacks including the sensitivity to the initial SOC value that could be inaccurately estimated and the accumulated error due to its use of integration. There are several new and improved methods which are based on neural networks, fuzzy logic, adaptive observers and extended Kalman filter (EKF) [8–12]. The proposed method in Refs [9-11], which is based on EKF, can predict the SOC of the Li-ion battery for HEVs and is known to be optimal for handling recursive mathematical equations in nonlinear systems such as those encountered in Li-ion batteries. However, none of these papers considered aging effects and capacity fade in Li-ion batteries.

Batteries lose a portion of their capacity in the process of aging [13]. It is important to recognize that characteristics such as SOC change in a short time frame during operation, while those such as capacity fade change in a longer time frame; yet, they have close correlations with one another. To correlate the SOC with capacity fade, requires a model to estimate the SOC accurately using model parameters that are adaptively updated during aging. Recently, in Ref. [14], a novel algorithm was proposed to update the parameters of a Li-ion cell model using EKF and their highest priority is to estimate each cell's voltage accurately. Ref. [15] presents an adaptive extended Kalman filter (AEKF) to estimate SOC based on cell voltage estimation. However, the algorithm focuses on covariance matching and the method does not cover aged cells. This article presents an improved method of using an optimization algorithm to update a Li-ion battery electrical model's parameters as an updated model for EKF to estimate SOC.

The paper is organized as follows, Section 2 presents an electrical model used for a $LiFePO_4$ cell in the paper. A review of the EKF is presented in Section 3. Section 4 contains a sensitivity analysis for electrical model elements regarding SOC error. This section also explains the proposed method for the model adaptive extended Kalman filter (MAEKF). Section 5 discusses the results of applying the proposed algorithm to an experimental model obtained from Ref. [5]. The paper concludes with a summary in Section 6.

2. Battery electrical modeling

SOC, as one of the most important informational aspects of a BMS, is an inner state of each cell [6] that cannot be measured directly during battery operation. As a result, estimating SOC is the only way to derive its value. To estimate this value, a model for the battery is needed. A variety of battery models are developed to capture Li-ion battery performance for various purposes; among them the equivalent circuit models and the electrochemical models are the most widely used in EV studies. The electrical circuit models use equivalent electrical circuits to show I–V characteristics of batteries by using voltage and current sources, capacitors, and resistors. Due to the remarkable relaxation effect seen in the Li-ion battery, its model requirements, including enough accuracy and covering different empirical conditions like working condition of EVs/HEVs, we select the model presented in [5] as the battery model-shown in Fig. 1. The energy balance circuit is a part of the model which delivers SOC to the voltage response circuit. In this model, the ohmic resistance R_o consists of the bulk resistance and surface layer impedance, accounting for the electrical conductivity of the electrolyte, separator and electrodes. The activation polarization is modeled by R_s and C_s, and the concentration polarization is presented by R_l and C_l.

To cover all practical conditions and consider a suitable level of complexity, the model's components are assumed to be a function of SOC, C-rate, and temperature. Moreover to increase accuracy, this model has separate operating functions for charging and discharging.

The electrical behavior of the practical model can be expressed as follows:

$$V_t = V_{oc} - V_{trans} - R_o I_L \tag{1}$$

$$V_{trans} = V_s + V_l \tag{2}$$

$$\dot{V}_s = -\frac{1}{R_s C_s} V_s + \frac{1}{C_s} I_L \tag{3}$$

$$\dot{V}_l = -\frac{1}{R_l C_l} V_l + \frac{1}{C_l} I_L \tag{4}$$

where V_t is the battery terminal voltage, V_{oc} is the battery open circuit voltage (OCV), I_L is load current. V_s and V_l are respectively the short and long time transient voltage responses for charging/discharging.

3. Extended Kalman filter

Kalman filter (KF) is a well-known estimation theory introduced in 1960 [16]. This filter provides a recursive solution through a linear optimal filtering to estimate systems' state variables. However, if the system is nonlinear, at each step, a linearization process will be applied to approximate the nonlinear system with a linear time varying (LTV) system. Using this LTV system in KF, would result in an extended Kalman filter (EKF) on a real nonlinear system [11]. The calculation process for a nonlinear system is with modeling:

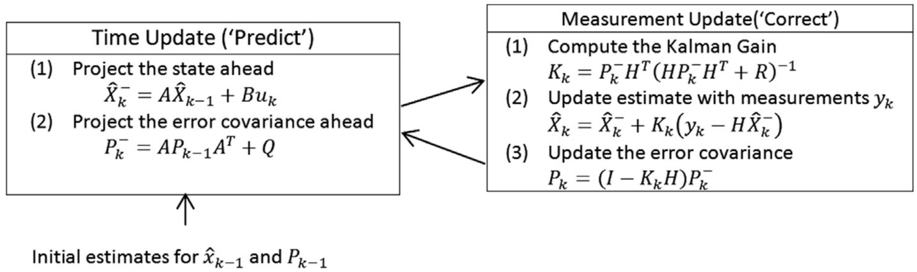

Fig. 2. Complete picture of the operation of the extended Kalman filter.

$$x_{k+1} = f(x_k, u_k) + w_k \tag{5}$$

$$y_{k+1} = g(x_k, u_k) + v_k \tag{6}$$

where Eq. (5) is the system dynamics represented in state equations, and Eq. (6) is the output equation of the system with a static relationship. Function $f(x_k,u_k)$, is a nonlinear transition function and $g(x_k,u_k)$ is a nonlinear measurement function. Vectors w_k and v_k denote process and measurement noise which are uncorrelated, zero-mean, white Gaussian, stochastic processes with covariance matrixes Q and R.

At each time step, matrices of $f(x_k,u_k)$, and $g(x_k,u_k)$ are linearized close to the operation point using the first order of a Taylor-series and the rest of the series is truncated. Assuming that $f(x_k,u_k)$, and $g(x_k,u_k)$ are differentiable at all operating points and $A_k = \partial f/\partial x|_{x=\hat{x}}$, $C_k = \partial g/\partial x|_{x=\hat{x}}$, EKF starts filtering with the best available information on the initial state $(\hat{x}_0^+)$ and error (P_0^+) covariance as shown in Eq. (7).

$$\hat{x}_0^+ = E[x_{01}], \quad P_0^+ = E\left[\left(x - \hat{x}_0^+\right)\left(x - \hat{x}_0^+\right)^T\right] \tag{7}$$

The EKF is summarized as Fig. 2 [17,18].

4. SOC estimation using MAEKF

For the efficient management and control of battery pack, an accurate estimation of SOC is needed by BMS. EKF is an optimum state estimator for nonlinear systems in which recursion is the fundamental feature of its operation. As EKF is formed in discrete space, Eqs. (5) and (6) are transformed to their discrete counterparts to estimate SOC in discrete space. Following the form of EKF, the state equations for the nonlinear system of the battery are obtained as $x_1 = V_s$, $x_2 = V_l$, $x_3 = \mathrm{SOC}$. State equations used in this paper for modeling battery behavior, are expressed in Fig. 3. SOC, in contrast to terminal voltage and current, is an inner state of the battery and should be estimated instead of directly measured. Linearized version of Eqs. (5) and (6) in discrete space are obtained in Eqs. (8) and (9) as shown below.

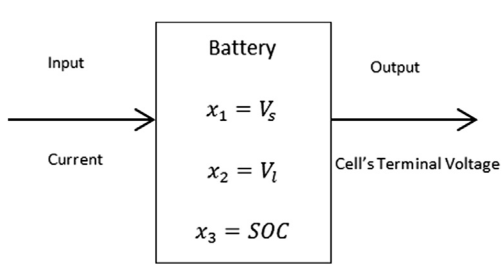

Fig. 3. Illustration of state equations.

$$x_{k+1} = A_k x_k + B_k I_{L,k} + w_k \tag{8}$$

$$V_t = y_k = C_k x_k + D_k I_{L,k} + v_k \tag{9}$$

The state vector for the model consists of three state variables as indicated in Eq. (10).

$$x_k = \begin{bmatrix} V_{s,k} \\ V_{l,k} \\ \mathrm{SOC}_k \end{bmatrix} \tag{10}$$

where SOC_k is the observation of SOC at time step k which is equal to Eq. (11):

$$\mathrm{SOC}_k = \mathrm{SOC}_{k-1} + \eta I_{\mathrm{L},k} \Delta t / C_{\mathrm{usable}} \tag{11}$$

In the above equation, Δt stands for sampling time, η is the columbic efficiency and C_{usable} is the usable capacity of the battery's available capacity. The observation equations of the discrete system are as follows:

$$A_k = \begin{bmatrix} e^{\frac{-\Delta t}{R_{s,k}C_{s,k}}} & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R_{l,k}C_{l,k}}} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$B_k = \begin{bmatrix} R_{s,k}\left(1 - e^{\frac{-\Delta t}{R_{s,k}C_{s,k}}}\right) \\ R_{l,k}\left(1 - e^{\frac{-\Delta t}{R_{l,k}C_{l,k}}}\right) \\ -\eta I_{L,k}\, \Delta t / C_{\mathrm{usable}} \end{bmatrix}$$

$$C_k = \left.\frac{\partial V_t}{\partial x}\right|_{x=\hat{x}_k^-} = \begin{bmatrix} -1 & -1 & \left.\frac{\partial V_{oc}}{\partial \mathrm{SOC}}\right|_{\mathrm{SOC}_k^-} \end{bmatrix}$$

$$D_k = [-R_{o,k}] \tag{12}$$

4.1. SOC estimation using EKF for an aged cell and sensitivity analysis

Parameters of an initial battery model are needed for state estimation of SOC using the EKF method. However, the accuracy of SOC estimation using EKF diminishes with battery age. To have precise estimation of a battery's SOC, an updated electrical model is needed for EKF.

A test is conducted to show the state estimation error of SOC using EKF method for an aged cell. The test is undertaken at room

Table 1
Mean values for electrical model's elements for NEW and the same cell after degradation (degraded cell).

	R_o (Ω)	R_s (Ω)	C_s (F)	R_l (Ω)	C_l (F)
New cell	8.2733 e−002	1.5115 e−002	8.3716 e+002	3.6291 e−002	4.7234 e+003
Degraded cell	1.0515 e−001	2.0230 e−002	8.3716 e+002	4.2902 e−002	4.7234 e+003

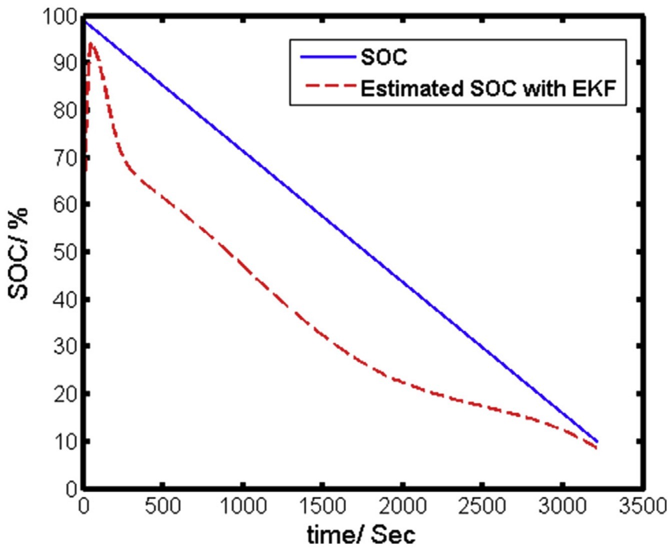

Fig. 4. Reference SOC and estimated SOC for a degraded cell with EKF (discharged with 1C).

temperature with discharging current 1C (1.1 A) on a degraded cell. The electrical characteristics of the test battery are assumed to be the equivalent of a new battery. Mean values for electrical elements of the new and degraded cell are indicated in Table 1. Fig. 4 presents results for SOC calculated by coulomb counting as a reference SOC versus the SOC estimated by EKF. According to this test's outcome, EKF's estimation will have almost a 30% difference compared with the reference SOC if the updated model is not used for the aged cell.

Moreover, to find out which impedance elements of the electrical model have the most impact on SOC estimation, a sensitivity

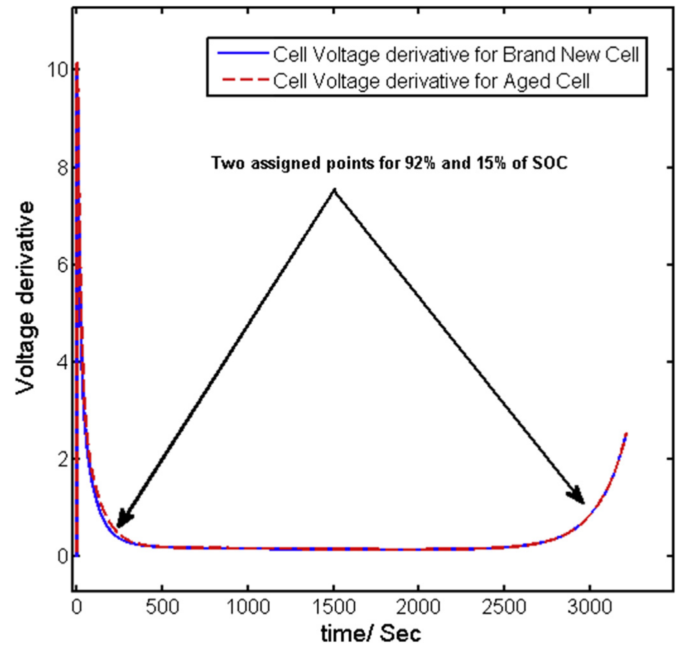

Fig. 6. Derivative of a cell's terminal voltage for a new cell and an aged cell (discharged with 1C at room temperature).

analysis is performed. To calculate the sensitivity of each parameter, the cell's other parameters are assumed to be same as the previous model. Sensitivity analysis results for all elements associated with impedance are presented in Fig. 5. This analysis shows that among all electrical elements in the voltage response circuit, SOC estimation error has the most sensitivity to R_o, R_s and R_l while capacitances do not have much effect on SOC estimation.

4.2. MAEKF approach

A close look at SOC − V_t variation on a new cell and the same cell after aging reveals that the terminal voltage has a sharp variation at two points. In the case of the examined cell, this sudden voltage variation happens at SOCs of 92% and 15% which are used as points of reference in this work. According to Eq. (1), V_t is the OCV of the cell deducted by transient voltages and voltage drop on cells

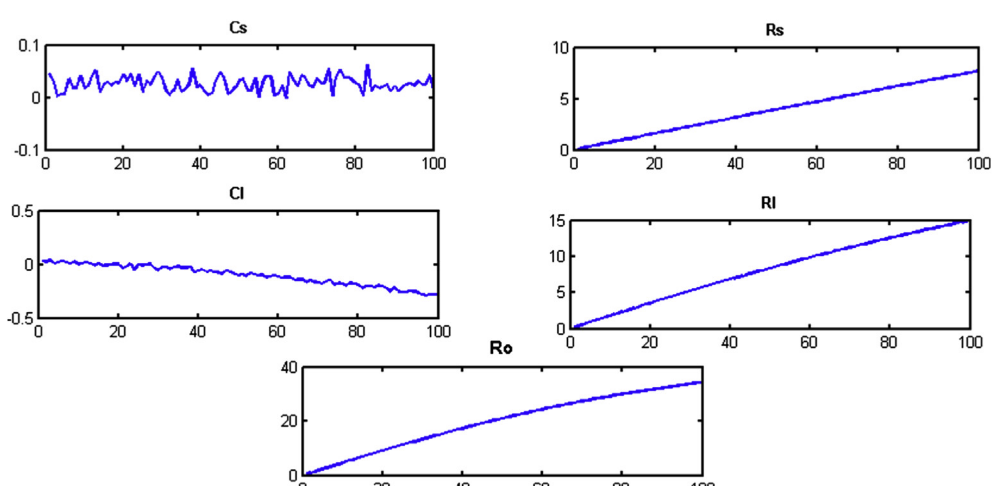

Fig. 5. Sensitivity analysis for C_s, R_s, C_l, R_l and R_o. *X*-axis is increment of the analyzed impedance element to EKF's model in %, *Y* axis is the estimated SOC's mean error in %.

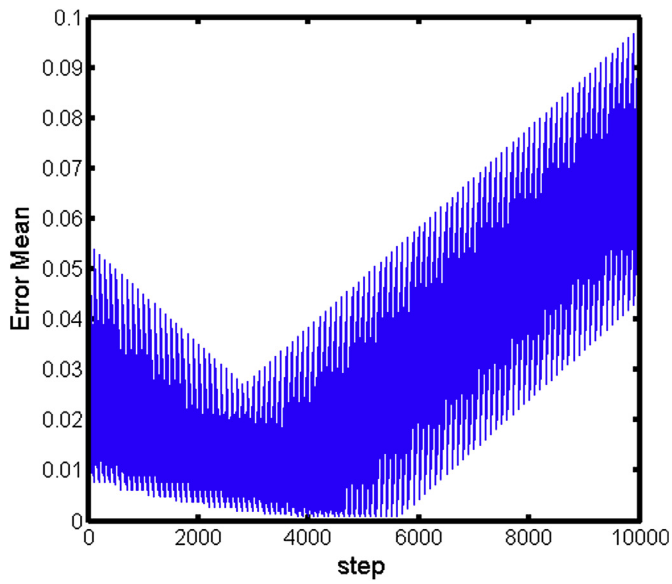

Fig. 7. Mean error for the optimization equation for two reference points.

internal resistance. Since R_o, R_s, C_s, R_l depend on the cell's SOC, V_t is a function of SOC as well.

$$V_t = h(\mathrm{SOC}) \tag{13}$$

Derivation of V_t in Eq. (13) gives:

$$\dot{V}_t = \dot{\mathrm{SOC}} * \dot{h}(\mathrm{SOC}) \tag{14}$$

Considering that $\dot{\mathrm{SOC}} = -I_L/C_{usable}$, Eq. (14) changes to:

$$\dot{V}_t = -\frac{I_L}{C_{usable}} * \dot{h}(\mathrm{SOC}) \tag{15}$$

$-\dot{V}_t$ for a new cell and an aged cell are shown in Fig. 6. There are two sudden changes in the cell's voltage derivative with respect to time while discharging with constant current. These two points are assumed as reference points from which their SOC can be determined from the cell's chemistry. Assigning SOC for the discharging period, sharp drops in $\dot{V}_t$ in the tested cell are seen at 92% and 15% of SOC.

As mentioned in Section 4.1 the electrical model is sensitive to R_o, R_s and R_l values in electrical model. In addition each of these terms are a function of SOC according to following equations [5]:

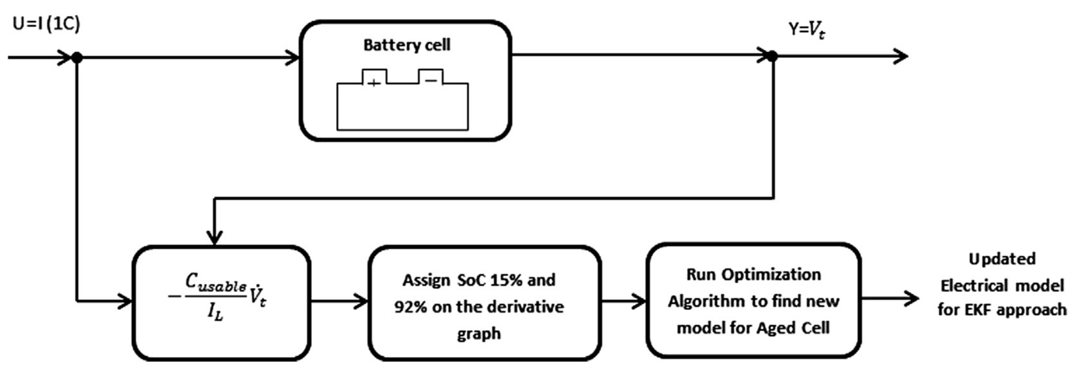

Fig. 8. Illustration of the MAEKF algorithm in a block diagram.

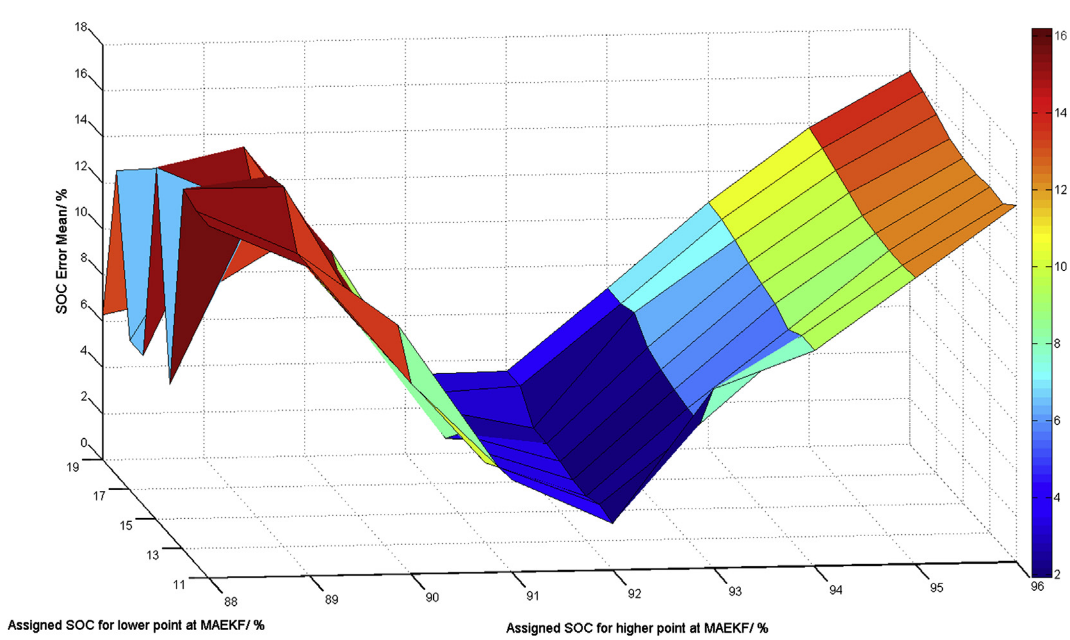

Fig. 9. Sensitivity analysis for the two assigned points in the optimization algorithm.

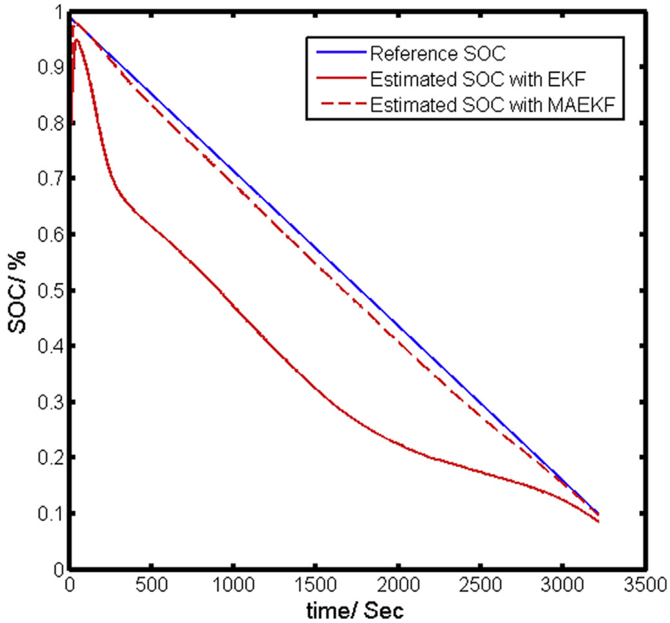

Fig. 10. SOC estimated with EKF and MAEKF for an aged cell (discharging current = 1C).

$$R_o = b_1 SOC^4 + b_2 SOC^3 + b_3 SOC^2 + b_4 SOC + b_5 \quad (17)$$

$$R_s = c_1 e^{-c_2 SOC} + c_3 \quad (18)$$

$$R_l = g_1 e^{-g_2 SOC} + g_3 + g_4 SOC \quad (19)$$

Thus, the above resistors are selected to be updated in EKF model using optimization, resulting in MAEKF.

The optimization method finds the minimum of Eq. (20) at each reference point.

$$(V_t - V_{oc} - V_{trans} - R_o I_L) \quad (20)$$

The mean error for two reference points is shown in Fig. 7 where at the X-axis the optimization variables R_o, R_s and R_l are varied incrementally within their range of:

$$\begin{aligned} &R_{o,\,initial} < R_o < 1.5R_{o,initial} \\ &R_{s,initial} < R_s < 2R_{s,initial} \\ &R_{l,initial} < R_l < 2R_{l,initial} \end{aligned} \quad (21)$$

where $R_{o,initial}$, $R_{s,initial}$ and $R_{l,initial}$ are the corresponding value of R_o, R_s and R_l for a brand new cell or the latest value of EKF model. As presented in Fig. 7, the mean error of the objective function using two reference points has many local minimums and optimization

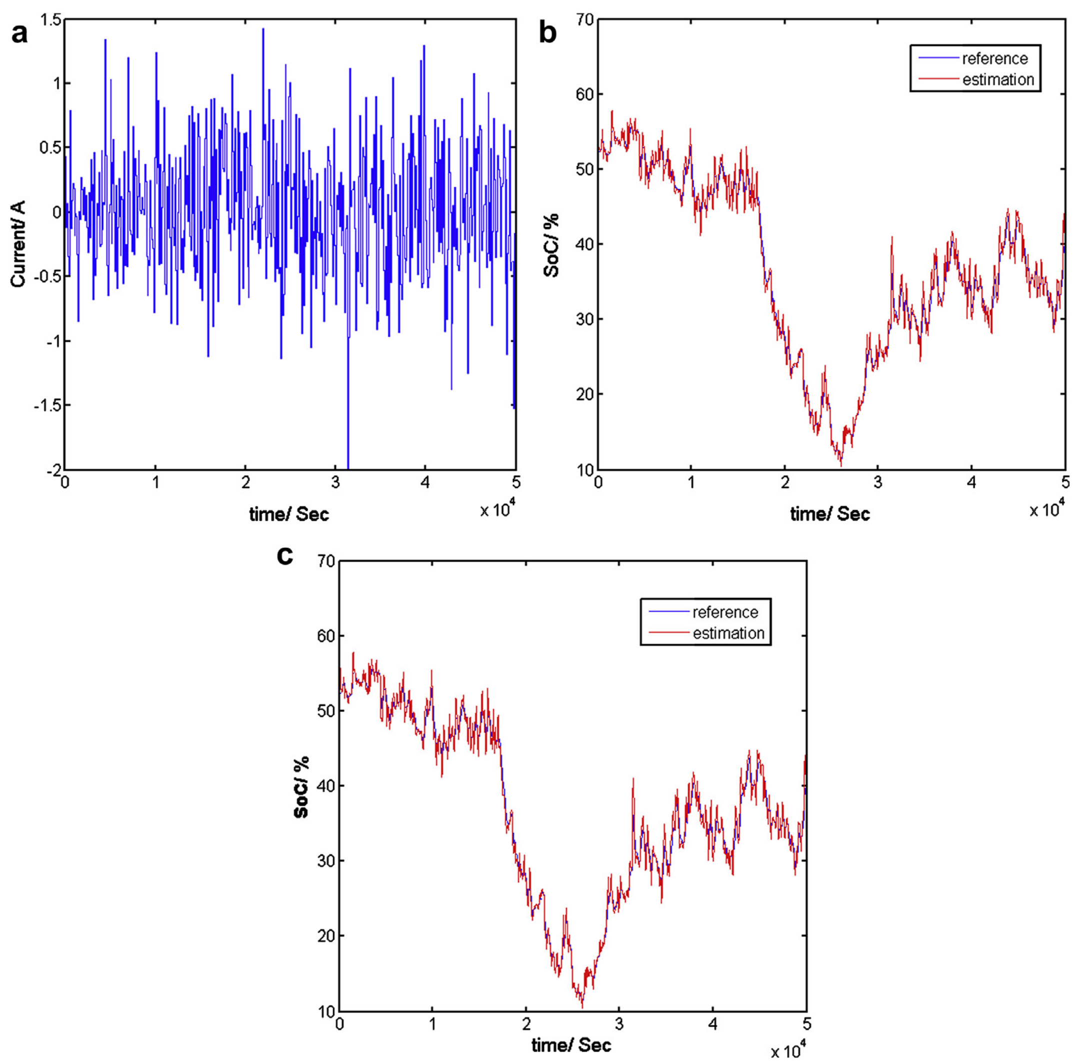

Fig. 11. (a) Current profile. (b). Degraded cell. (c). Old cell. SOC estimation for a degraded and an aged cell with the current profile presented in (a).

algorithms can trap in any of them. To overcome this difficulty and to find a new model for an aged cell, a brute-force approach with limitations presented in Eq. (21) has been used as optimization method.

In addition to the above optimization, to achieve a more accurate SOC estimation, C_{usable} is updated while the cell is under load with the method suggested in Ref. [19] except that instead of real SOCs, SOCs estimated by EKF are used.

Based on the foregoing explanations, this method can be summarized in the following steps:

1) Discharge the cell with constant current while measuring the cell's terminal voltage
2) Calculate the derivative of the voltage measured in step one
3) Assign 92% and 15% SOC as two reference points of the voltage derivative
4) Assign more SOCs using reference points and coulomb counting (optional)
5) Perform optimization to obtain the updated model.
6) Assign the updated model to EKF.

Fig. 8 presents an implementation flowchart of the MAEKF algorithm.

4.3. MAEKF sensitivity to reference SOCs

The optimization algorithm in MAEKF method uses the cell's measured terminal voltage derivative to allocate92% and 15% SOCs to two points in the V_{cell} (SOC) equation. A new model is produced based on these assigned SOCs and the old model, though it is possible that real SOCs for these two points are different from the assigned SOCs. This inaccuracy will produce an error in estimated SOC. To find out how sensitive the MAEKF's estimation is to reference points, a sensitivity analysis on a degraded cell is performed as shown in Fig. 9. For a degraded cell, $92 \pm 4\%$ and $15 \pm 4\%$ values are assigned as reference SOCs in MAEKF algorithm and the SOC estimation error mean is calculated. In this sensitivity graph, X and Y axes are assigned SOC instead of 92% and 15% in optimization algorithm for the MAEKF, respectively. This result demonstrates that the mean error of the estimated SOC is higher if assigned values for the upper reference point are different than 92%. Thus, the accuracy of the SOC estimate is more sensitive to the accuracy of assigned SOC at 92% rather than assigned SOC at 15%.

5. Experimental results

The proposed method is tested at room temperature on an A123 Systems' APR18650m1 $LiFePO_4$ battery with a 1.1 Ah nominal capacity. A new electrical model is founded after applying an optimization algorithm on an aged cell. Later on, MAEKF estimates SOC.

The observed SOC and estimated SOC, using EKF and MAEKF methods for a single aged cell are shown in Fig. 10. Discharging current for this test is constant and equal to 1C. It is apparent from Fig. 10.that the SOC estimated by MAEKF is more accurate than EKF an aged cell.

For a degraded cell, and an aged cell with a current profile presented in Fig. 11a, the SOC estimation is shown in Fig. 11b and c.

Table 2
SOC estimation error of differently pre-aged cells in the profile plotted in Fig. 11.

SOC/ %	Mean of error	Variance of error
Degraded cell	0.06	1.15012
Old cell	−0.12	1.1588

For this test, the mean and variance of the SOC estimation error are given in Table 2. The reference SOC in this comparison is calculated through the coulomb counting method.

6. Discussion and conclusion

EKF is an accurate method to estimate SOC for Li-ion batteries. This estimation is accurate when the model predicts the cell properly. As a battery ages, the model cannot predict the cell's output accurately; correspondingly EKF's estimation will no longer be reliable. To overcome this drawback and improve the accuracy and reliability of estimation, a novel method for updating the battery model used by EKF for aged Li-ion batteries is proposed. Model Adaptive EKF (MAKEF) is an inline and on-board method to update the electrical model for a Li-ion cell. One of the salient points of this method is the ability to estimate SOC for individual cells and battery packs with high accuracy even after substantial aging. The proposed method can be used in place of cell screening by finding an electrical model of each cell with the same chemistry. The feasibility and verification of MAEKF for estimating SOC are made through several experiments.

Sensitivity analysis of the electrical model reveals that the accuracy of SOC estimated by EKF is mostly dependent on the values of three resistances R_o, R_s and R_l. As a result, these parameters are selected to be updated in optimization algorithm using the proposed optimization method. The optimization algorithm uses a cells measured terminal voltage derivative to allocate SOCs of 92% and 15% to two points in the V_{cell} (SOC) equation. Based on these assigned SOCs and using old values, new values for electrical elements are procured. As these two points are not fixed for different cells with the same chemistry, a sensitivity analysis for the assigned points shows that the accuracy of SOC estimated by EKF from the updated model is more sensitive to the accuracy of the assigned SOC at 92%. Moreover, the estimation accuracy of updated model is better in the case that the assigned SOCs to the updated model are greater than real cell SOCs compared with being less than real cell SOC. This confirms that the proposed method is more practical since the aged cell has less SOC value than its assigned SOC at both 92% and 15%. Based on mentioned results in this manuscript, the proposed method guarantees that the error of estimated SOC for an aged cell does not exceed 4%.

Acknowledgments

This work was supported in part by the University of Hawaii Renewable Energy and Island Sustainability (REIS) Program, and by the US Department of Energy grant, DE-OE0000394.

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